



CS F425: Deep Learning

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Siamese Network

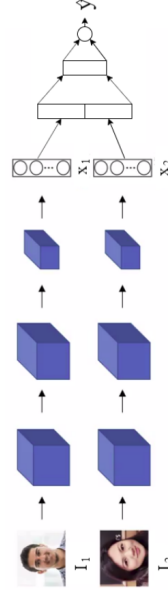


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<http://ktiwari.in/dl>

Siamese Network

Learn features using twin of an architecture.



- Weights are shared (same)
- Output could be the distance or classification
- Threshold could be used to determine if class is same or not?

Hinge Loss

- Maximization of $\|p - q\|^2$ is equivalent to minimization of

$$\infty - \|p - q\|^2$$

- that is similar to minimization of $M - \|p - q\|^2$
- Smaller value of M is used for multiclass setting

$$\text{minimize}(m - \|p - q\|^2)$$

- However a **hinge** is better

$$L(P, Q) = \max(0, m - \|p - q\|^2) \rightarrow HL$$

Contrastive Loss that need to be minimized is

$$L = y \times EL + (1 - y) \times HL$$

Metric Learning

Learning in many applications depends upon **proximity measures**

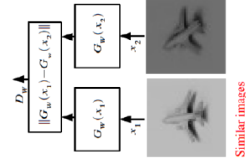
- Distance measure is used to find dissimilarity between pattern representations. More similar patterns should be near
- **Metric** "distance" measure $d(x, y) \geq 0$ has following properties
 - 1 **Positive reflexivity** $d(x, x) = 0$, therefore when $d(x, x) = 0 \rightarrow x = y$
 - 2 **Symmetry** $d(x, y) = d(y, x)$
 - 3 **Triangular Inequality** $d(x, y) \leq d(y, z) + d(z, y)$
- **Minkowski metric**:

$$d^m(X, Y) = \left(\sum_{k=1}^d |x_k - y_k|^m \right)^{\frac{1}{m}}$$

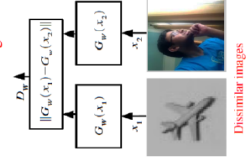
- Manhattan distance or L_1 uses $m = 1$, Euclidean or L_2 has $m = 2$
- L_0 is number of non-zero elements and L_∞ is maximum

Siamese Loss

Make this small



Make this large



- Contrastive loss

$$L = \sum \text{loss of positive pairs} + \sum \text{loss of negative pairs}$$

- Positive pairs $L(P, Q) = \text{minimize} \|p - q\|^2 \rightarrow EL$
- Negative pairs $L(P, Q) = \text{maximize} \|p - q\|^2$

Training: need of margin and the Triplet loss

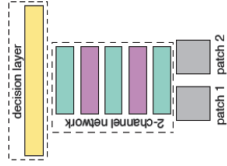
Negative examples are much larger than positive ones.

- Training would require a pair of images and 1/0
 With Anchore, Positive and Negative: $(A, P, 1), (A, N, 0), (P, N, 0), \dots$
- $D(A, P) = \|x_a - x_p\|^2$ and $D(A, N) = \|x_a - x_n\|^2$
- $D(A, P) \leq D(A, N)$ therefore we can have $D(A, P) + \alpha \leq D(A, N)$
- Or equivalently $D(A, P) - D(A, N) + \alpha \leq 0$
- Let
- Loss

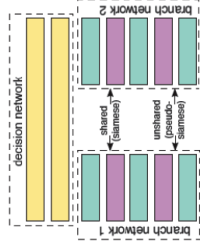
$$L(A, P, N) = \max(D(A, P) - D(A, N) + \alpha, 0)$$

$$J = \sum_{i=1}^m L(A^i, P^i, N^i)$$

Architecture Varieties



Inputs are merged right at the onset



Inputs are first embedded independently, then merged.

Online Semi Hard Negative Mining

- For a given network, we choose 1000 triplets randomly.
- Pass these 1000 triplets through the network and find $D(A, P)$ and $D(A, N)$ for each triplet.
- Select the triplets which satisfies the following conditions:
 - ▶ $D(A, N) - D(A, P) < \alpha$. These are the triplets which are hard and will produce a loss for the optimization of the network.
 - ▶ $D(A, N) > D(A, P)$. Discards the outliers.
- Out of the 1000 random triplets, we only train the network with those which satisfy above two conditions and then repeat this process.

Design governs by what empirically performs well on the task at hand.

Thank You!

Thank you very much for your attention!